ONLINE SUPPLEMENT

Continuity of Genetic and Environmental Influences on Cognition across the Life Span:

A Meta-Analysis of Longitudinal Twin and Adoption Studies

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Online Supplement

First Set of Sensitivity Analyses

In a first set of sensitivity analyses, we examine whether the lifespan age trends obtained in the main analyses persist after including controls for whether the cognitive tests changed across longitudinal measurement occasions, and whether the effect sizes were computed based on behavioral genetic models that were unconstrained or trimmed in some way. We chose the best fitting continuous age-based models for each outcome from Tables 4 and 5 and added two dummy coded control variables: the first representing constant (0) vs. changing (1) indicators, and the second representing whether the effect size was obtained from an unconstrained (0) vs. a trimmed (1) Model.

Coding

Our original inclusion criteria required that the longitudinal measurements be of the same cognitive ability at each time point (e.g. general intelligence measured at both occasions, or processing speed measured at both occasions). If the same measure (e.g. the WISC, or the digit symbol test) was used to measure the ability at both occasions, the associated effect size was considered to be derived from a constant indicator. If different tests of the same cognitive ability (e.g. the Stanford Binet followed by the WISC) were used at different occasions, the effect size was considered to be derived from changing indicators.

A model was considered unconstrained if it was derived from a longitudinal correlated factors model (Figure 3) with all parameters $(a_1, c_1, e_1, a_2, c_2, e_2, r_a, r_c, and r_e)$ freely estimated, or a statistically equivalent model (e.g. a Cholesky model with all parameters freely estimated). A model was considered trimmed if an A, C, or E factor was dropped/not estimated, or a parameter was either implicitly or explicitly fixed (e.g. to 0 or 1), excluded, or otherwise constrained.

Results

Results are presented in Table S1. There were statistically significant associations between the two control variables and the effect sizes. Phenotypic stability, genetic stability, and nonshared environmental stability were lower when indicators changed. Shared environmental stability was

markedly higher when effect sizes were derived from trimmed models. The genetic contribution to phenotypic stability, but not genetic stability itself, was higher when effect sizes were derived from trimmed models. The nonshared environmental contribution to phenotypic stability was significantly. although not appreciably, lower both when indicators changed and when effect sizes were derived from trimmed models. Importantly, the age-based trends obtained after controlling for these effects were extremely similar to those reported in the main text. For phenotypic stability, the horizontal asymptote was .751, the scaling factor was .530, and the growth rate was -.193 compared to .783, .559, and -.123 in the main analyses. For genetic stability, these estimates were .980, .952, and -.266 compared to .993, 1.166, and -.222 in the main analyses. For shared environmental stability, these estimates were .850, .621, and -.498, compared to .854, .546, and -.346 in the main analyses. Finally, for nonshared environmental stability, the intercept and slope were .101 and .007 compared to .053 and .007 in the main analyses. For the genetic and environmental contributions to phenotypic stability, the parameters were similarly comparable across main and sensitivity analyses.

Table S1. Parameter estimates and fit statistics for models of lifespan age trends in stability with controls for constant vs. changing indicators and unconstrained vs. trimmed models.

for constant vs. changing indicators and unconstrained vs. trimmed models.												
	Constant	Age growth		Constant (0) vs.	Unconstrained (0) vs.							
		(linear or		Changing (1)	Trimmed (1) Model							
		exponential)		Indicators								
Dependent Variable	b_0 (SE)	b_1 (SE) b_2 (SE) b_6 (SE)		b ₇ (SE)								
Phenotypic Stability	.751	.530	193	063 (.024)**	.052 (.032)							
(exponential age function)	(.021)**	(.033)**	(.027)**									
Genetic Stability	.980	.952	266	166 (.073)*	.013 (.041)							
(exponential age function)	(.040)**	(.200)**	(.033)**									
Shared Environmental	.850	.621	498	060 (.033)†	.406 (.040)**							
Stability	(.042)**	(.083)**	(.144)**									
(exponential age function)												
Nonshared Environmental	.101	.007		054 (.025)*	039 (.022)†							
Stability	(.026)**	(.001)**										
(linear age function)												
	72 0	62.4	105	005 (001)	1.40 (00.5) ded							
Genetic Contribution	.539	.634	197	025 (.021)	.140 (.025)**							
(exponential age function)	(.023)**	(.032)**	(.035)	000 (000)	0.61 (0.55)							
Shared Environmental	.269	004		032 (.023)	061 (.055)							
Contribution	(.023)**	(.001)**										
(linear age function)	002	000		014 (004) **	017 (000) **							
Nonshared Environmental	.023	.002		014 (.004)**	017 (.006)**							
Contribution	(.004)**	**(000.)										
(linear age function)												

(linear age function)
Note: Note: †p<.10, *p<.05, **p<.01.

Second Set of Sensitivity Analyses

A reviewer indicated that it would be advantageous to include studies from the International Longitudinal Twin Study and the Florida State Twin Registry, as these are two well-known longitudinal studies. The published articles that we identified for these studies (Byrne et al., 2007; Hart, Logan, Soden-Hensler, Kershaw, Taylor, & Schatschneider, 2013) did not meet criteria for inclusion in our main meta-analysis because we had originally determined that the phenotypes examined were better characterized as measures of academic achievement, rather than cognitive ability. (Admittedly, the distinction between crystallized intelligence and academic achievement can often be ambiguous.) To examine whether results would change by including effects sizes from these two studies, we therefore conducted a second set of sensitivity analyses on a larger dataset that included them. We also included effect sizes from the two other articles that we had come across during our primary literature search but originally excluded because we determined that the phenotypes examined were measures of achievement. These were Kovas et al. (2007), and Tucker-Drob (2012). Although Tucker-Drob (2012) did not include the relevant longitudinal correlations that we needed, we had access to the original data, and were therefore able to obtain these correlations. For all four of the studies added, we only made use of effect sizes derived from data in which achievement was measured using an objective test. Teacher ratings of achievement and course grades were not included. In total, this amounted to an addition of 22 pairs of time points and measures. The average age at initial assessment was 7.49 years (range = 4.4 to 10 years), and the average time interval between assessments was 1.82 years (range = 1 to 4 years). These additional datapoints were derived from an additional 522 monozygotic twin pairs reared together and 869 dizygotic twin pairs reared together above and beyond those contributing data to the main analyses.

Because academic achievement pertains most directly to the school years, we decided it most appropriate to focus specifically on the age- and time-based trends in childhood (i.e. age less than 18). We included data from academic achievement tests, and analyzed the data using the same models as those used to produce the parameter estimates from Table 6 in the main text, with the following adjustments: 1) we excluded the age × time interactions for phenotypic stability and nonshared environmental stability as

these terms were not statistically significant in the original analyses, 2) we added three dummy coded predictors: constant vs. changing indicators, unconstrained vs. trimmed model, and cognitive ability vs. academic achievement.

Coding

We created a new dummy-coded variable to indicate whether effect sizes in our meta-analytic dataset were reflective of cognition (0) or achievement (1). Thus, all effect sizes analyzed in the original analyses reported in the main body text were coded as 0, and all effect sizes added for this sensitivity analysis were coded as 1.

Results

Results are presented in Table S2. There were indeed statistically significant associations between our control variables and the effect sizes. Results indicated that genetic stability was higher when effect sizes were derived from trimmed models and lower for academic achievement than for cognition. Nonshared environmental stability was lower when effect sizes were derived from trimmed models, and appreciably (although only marginally significantly, p=.059) higher for academic achievement than for cognition. Importantly, results obtained after controlling for these effects were extremely similar to those reported in the main text. Stabilities increased with age and decayed with time. As in the main analyses, time-based decay of both genetic stability and shared environmental stability was most pronounced in early childhood. This age × time interaction was statistically significant at p<.05 for genetic stability, and marginally significant (p=.074) for shared environmental stability.

Table S2. Parameter estimates and fit statistics for simultaneous childhood age and time trends in stability of cognition and achievement, with controls for constant vs. changing indicators, unconstrained vs. trimmed models, and cognition vs. achievement.

	Constant	Age growth		Time Decay		Age ×	Constant	Unconstra	Cognitive
		(linear or		(exponential)		Time	(0) vs.	ined (0)	Ability (0) vs.
		expon	ential)				Changing	vs.	Academic
							Indicators	Trimmed	Achievement
								(1) Model	(1)
Dependent Variable	b_0 (SE)	b_1 (SE)	b_2 (SE)	b_3 (SE)	b ₄ (SE)	b_5 (SE)	b_6 (SE)	b ₇ (SE)	b ₈ (SE)
Phenotypic Stability	.460	.670	578	472	592		.030 (.120)	.037	.026 (.071)
(exponential age function)	(.077)**	(.190)**	(.375)	(.136)**	(.107)**			(.040)	
Genetic Stability	1.029	1.494	268	680	.093 (.240)	239	012	.105	159 (.036)**
(exponential age function)	(.138)**	(.275)**	(.133)*	(.098)**		(.099)*	(.038)	(.025)**	
Shared Environmental	.788	.879	362	-1.276	-1.126	122	.155	.063	.021 (.029)
Stability	(.088)**	(.156)**	(.099)**	(.329)**	(.310)**	(.068)†	(.085)†	(.074)	
(exponential age function)									
Nonshared Environmental	045	.016		372	760		.044 (.087)	099	.140 (.074)†
Stability	(.131)	(.011)		(.219)†	(.183)**			(.038)**	
(linear age function)									

Note: †p<.10, *p<.05, **p<.01.

References

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